Segmentation of Satellite Images in Optoelectronic System

ANDREY S. OSTROVSKY, ERNESTO PINO-MOTA, DEMAR SEVERIANO-CARRILLO, EDGAR HERNÁNDEZ-GARCÍA
Facultad de Ciencias Físico Matemáticas
Benemérita Universidad Autónoma de Puebla
A. P. 1152, 70000, Puebla, Pue.
MEXICO

Abstract: The problem of segmenting the satellite images into homogeneous texture regions that correspond to the different classes of terrestrial surface is considered. It is shown that this problem may be successfully solved by using the method of spectral synthetic discriminant functions recently proposed by the authors for classification of random image fields and realized by means of a rather simple optoelectronic technique. The experimental results of segmenting the true satellite images are given.

Key-Words: Image Segmentation, Image Classification, Synthetic Discriminant Functions, Optical Image Processing

1 Introduction

One of the central problems in automatic processing of satellite images is to segment the given image into homogeneous texture regions corresponding to different classes of the terrestrial surface such as different urban zones, mountainous zones, wooded zones, agricultural zones, aquatic zones, etc. [1]. A specific feature of this problem is in the fact that the images to be classified have fundamentally random within-class variations so that they must be viewed as being perfectly random or stochastic. In this situation, one is better off talking about the random image field and not the image itself, i. e., as a deterministic function of space. Recently we proposed a new method for classification of such images in which we use the special discriminant functions being synthesized to separate linearly the power spectra of random image fields of different classes [2,3]. We refer to this method as spectral synthetic discriminant function (SSDF) method. In this paper, we show how the SSDF method realized by means of a rather simple optoelectronic system may be used for segmenting the satellite images.

2 SSDF Method

We consider a certain image of the nth class $(n = 1,..., N)$ as the 2-D kth $(k = 1,..., K)$ sample function $f_{nk}(x, y)$ of a stationary and isotropic random field $f_n(x, y)$ with a power spectrum

$$S_n(\rho) = \lim_{R\to\infty} \frac{1}{R} \left\langle \left| F_{nk}(\rho,\theta) \right|^2 \right\rangle , \tag{1}$$

where

$$F_{nk}(\rho,\theta; R) = \int_0^R \int_0^{2\pi} f_{nk}(r,\varphi) \times \exp[-i2\pi r\rho \cos(\varphi - \theta)] r\mathrm{d}r\mathrm{d}\varphi , \tag{2}$$

is the finite Fourier transform of $f_{nk}(x, y)$ over the domain of radio R occupied by the image, (r,φ) and (ρ,θ) are the polar coordinates in the spatial and spatial-frequency domains respectively, and the angular brackets denote the expected value operation over the ensemble index k. Taking for granted the hypothesis of linear independence among the power spectra $S_n(\rho)$ for different classes, we can define the SSDFs as follows:

$$h_m(\rho) = \sum_{l=1}^{N} a_{ml} S_l(\rho), \quad m = 1,..., N, \tag{3}$$

$$\int_0^\infty S_n(\rho) h_m(\rho) \mathrm{d}\rho \equiv \delta_{nm} , \tag{4}$$

where δ_{nm} is the Kronecker symbol. Once the SSDFs have been calculated in accordance with Eqs. (3) and (4), a procedure for classifying the unknown sample image $f_{0k}(x, y)$ is to verify identity (4) for every m when substituting for $S_n(\rho)$ the power spectrum $S_0(\rho)$ of corresponding image field $f_0(x, y)$ [2]. As can be seen from Eq. (3), in order to determine the SSDFs, is necessary to know each power spectrum given by Eq. (1); this presupposes averaging over the infinite ensemble of infinitely extensive sample images. Actually, we always have available a finite number of finitely extensive sample images, a fact that leads to the statistical formulation of the problem.

The quantity that can be directly measured in an experiment is the sample power spectrum integrated in the azimuthal direction,

$$\hat{S}_{nk}(\rho;R)=\frac{1}{2\pi R}\int_0^{2\pi}\left|F_{nk}(\rho,\theta;R)\right|^2 \mathrm{d}\theta\,. \quad (5)$$

In the stage of SSDF synthesis, when we commonly dispose a sufficiently large number of sample images, the consistent estimate of power spectrum $S_n(\rho)$ can be obtained by averaging the sample spectra (5) over the ensemble index k:

$$\hat{S}_n(\rho)=\frac{1}{K}\sum_{k=1}^{K}\hat{S}_{nk}(\rho;R)\,. \quad (6)$$

In the stage of classification, usually just one sample image is available, so that with due regard for Eq. (3), the identity (4) takes the form

$$\sum_{l=1}^{N} a_{ml}\int_0^{\infty}\hat{S}_{nk}(\rho;R)\hat{S}_n(\rho)\mathrm{d}\rho = u_{nmk}\,, \quad (7)$$

where u_{nmk} is the sample value of some random variable u_{nm}. To maximize the reliability of correct classification it is obvious to require that

$$\langle u_{nm}\rangle=\delta_{nm} \quad (8)$$

and

$$\mathrm{Var}[u_{nm}]=\min_{a_{ml}}\mathrm{Var}[u_{nm}(a_{ml})]\,. \quad (9)$$

This can be readily achieved by applying for calculating the SSDFs the well known least-square technique [3]. Once the SSDFs have been calculated in this way, the decision on the class to which the sample image $f_{0k}(x,y)$ belongs can be made according to index m of the largest value

$$u_{0mk}=\int_0^{\infty}\hat{S}_{nk}(\rho;R)\sum_{i=1}^{N}a_{ml}\hat{S}_n(\rho)\mathrm{d}\rho\,. \quad (10)$$

3 Optical Realization

As appears from the previous section, the fundamental problem with practical realization of the SSDF method is calculating the sample power spectrum given by Eq. (5). For this purpose the coherent optical Fourier processor shown in Fig, 1 may be employed.

As well known [4], if in the object plane of this processor a transparency with amplitude transmitance $f_n(x,y)$, within a finite domain D of radio R is placed, then the intensity distribution of light field registered by the CCD detector array in the back focal plane of the Fourier transforming lens is given by

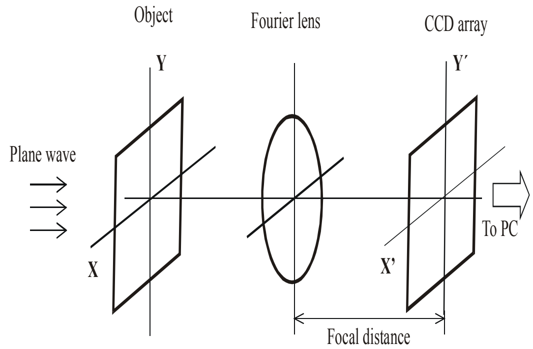

Fig.1 Optical Fourier processor.

$$I_{nk}(p,q;D)\propto\left|\iint_D f_{nk}(x,y)\right.$$
$$\left.\times\exp[-i2\pi(xp+yq)]\mathrm{d}x\mathrm{d}y\right|^2, \quad (11)$$

where $p=x'/\lambda f$, $q=y'/\lambda f$, λ is the wavelength of illumination, and f is the focal length of the lens. Using the polar coordinates for input and output planes of the Fourier processor, Eq. (10) may be rewritten as follows:

$$I_{nk}(\rho,\theta;R)\propto\left|\int_0^R\int_0^{2\pi} f_{nk}(r,\varphi)\right.$$
$$\left.\times\exp[-i2\pi r\rho\cos(\varphi-\theta)]r\mathrm{d}r\mathrm{d}\varphi\right|^2. \quad (12)$$

Comparing the latter equation with Eqs. (2) and (5), we came to conclusion that the sample power spectrum $\hat{S}_{nk}(\rho;R)$ may be easily calculated in any PC-compatible system connected with CCD array.

4 Experimental Results

We performed a physical simulation on segmentation of true satellite images into homogeneous regions that correspond to four different classes of terrestrial surface, to wit, “sea”, “mountains”, “crops” and “settlement”. An example of such a photograph is shown in Fig. 2.

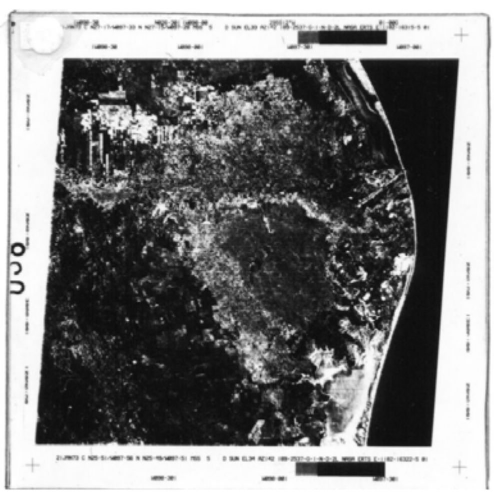
Fig.2. True satellite image used in the experiment.

Each class of texture images to be classified was considered a spatially stationary and isotropic random filed.

The experimental setup is sketched schematically in Fig. 3. The image to be processed in this setup were previously converted into numerical files using a standard scanning technique. To provide the capture of the digitalized images into the optical Fourier processor the liquid crystal spatial light modulator HOLOEYE-LC2002 (800 × 600 pixels) controlled by PC was used. The detection of the light distribution in the output plane of the Fourier processor was realized by means of the CCD camera SONY-SSC-M374 (768 × 494 pixels).

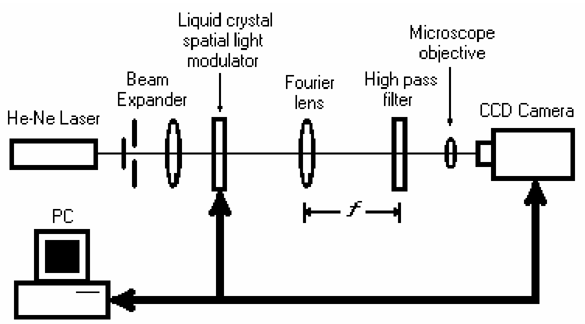

Fig. 3. Experimental setup

In our experiments, at stage of SSDFs synthesis, we used 50 images of 10 × 10 mm for each of four classes. At the stage of segmentation we used the composed full-scale image of 100 × 100 mm and realized its 2-D scanning by an aperture of 5 × 5 mm with a discrete step of 5 mm. At every step of image scanning the corresponding texture image was classified in accordance with the SSDF method. Calculation of SSDFs and values u_{0mk} (see Eq. (9)) was realized in a PC-system using a specially designed software. Decision on image class at every step of scanning was made on the basis of thresholding the output data. If one or more than one of u_{0mk} values had exceeded the threshold, the corresponding image region was considered to be unclassified. The result of four-class segmentation that corresponds to the satellite image in Fig. 2 is shown in Fig. 4. The regions of the result image labeled by "0" correspond to unclassified images. As can be seen, in the main these regions correctly repeat the true shape of the boundaries between terrestrial surface images of different classes, but, in certain cases, they occupy a rather large area of the photograph. The latter can be explained by the fact that, in reality, our satellite image contains texture images of more than four classes mentioned above (e.g., regions of the terrestrial surface covered by clouds),

2	2	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	1
0	0	0	0	4	4	4	0	0	0	3	3	0	0	0	1	1	0	1	1
0	4	0	4	0	4	4	4	0	3	3	3	3	0	0	0	0	1	1	1
0	4	4	0	4	0	0	0	0	3	3	3	3	3	0	0	0	1	1	1
4	4	4	4	0	0	0	0	3	3	3	3	3	3	3	0	0	0	1	1
0	4	4	4	0	0	0	0	3	3	3	3	3	3	3	3	0	0	1	1
0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	1	0	0
0	0	3	3	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	1
0	0	0	0	0	0	0	3	3	3	0	3	3	3	0	0	0	0	0	1
0	0	0	0	0	0	0	3	3	3	3	3	3	3	0	0	0	0	0	1
0	0	1	0	0	0	0	0	3	3	3	3	3	3	0	0	0	0	0	1
2	0	0	1	0	0	4	0	3	3	3	3	3	3	0	0	0	0	1	1
2	2	0	0	0	4	4	0	3	3	3	3	3	3	0	0	0	0	1	1
2	2	2	0	0	0	4	4	0	3	3	3	3	3	0	0	0	0	1	1
2	2	2	2	0	0	0	0	0	3	3	3	3	0	1	1	0	0	1	1
2	2	2	2	0	0	1	0	0	0	3	3	0	0	0	1	0	0	1	1
2	2	2	2	2	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1
2	2	2	2	2	2	0	0	1	0	0	0	1	1	0	0	0	0	1	1
2	1	2	2	2	2	2	0	0	0	0	0	1	0	0	1	0	0	1	1
2	2	2	2	2	2	0	1	1	1	0	0	0	0	0	0	0	1	1	1

Fig. 4. Labeled map of the satellite image shown in Fig. 2. Labels: 1 – "sea", 2 – "mountains", 3 – "crops", 4 – "settlement", 0 – "unclassified image".

5 Conclusions

As has been shown the problem of segmenting the satellite images into homogeneous regions that correspond to different classes of the terrestrial surface may be successfully solved by using the SSDF method of random image field classification realized by means of rather simple optoelectronic technique. The authors gratefully acknowledge the support of National Council for Science and Technology of Mexico (CONACYT) under project 36875-E and the support of Puebla Autonomous University (BUAP) under project II68G02.

References:

[1] H.-S. Wu, J. Qian, and J. Barba, A classified algorithm for segmentation of multispectral images, *Journal of Imaging Science and Technology*, Vol. 39, 1995, pp. 26-30

[2] A.S. Ostrosvsky, E. Pino-Mota, Classification of random image fields using synthetic discriminant functions: spectral statistical approach and its computer-optical realization, *Optical Review*, Vol. 5, 1998, pp. 219-225

[3] A.S. Ostrovsky, E. Pino-Mota, J. I. Palma-Cuatianquiz, Optical classification of random image fields using spectral synthetic discriminant functions, *Optics and Lasers in Engineering*, Vol. 40/1-2, 2003, pp. 43-53.

[4] J.W. Goodman, *Introduction to Fourier Optics*, McGraw Hill, 1986.